THEORETICAL ADVANCES



A biologically inspired framework for contour detection

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Abstract In this paper, we present a simple and efficient biologically inspired edge detection algorithm which attempts to model some structural features of the Human Visual System. More precisely, our edge detection approach attempts to model the dynamic retina concept, i.e., the natural saccadic eye movement process which redirects the fovea's attention from one point of interest to another within the image along with the inherent topological log-polar transformation (with its space-variant resolution) of the retinal image into its cortical projection. The experiments, reported in this paper and conducted on the Berkeley Segmentation Dataset, demonstrate that the proposed biologically inspired contour detection method performs well compared to the best existing state-of-the-art edge and contour detection methods recently proposed in the literature.

Keywords Berkeley Dataset (BSDS300) · Biologically inspired edge or contour detection · Cortical image · Dynamic retina concept · F-measure · Human visual system (HVS) · Log-polar mapping · Saccades

1 Introduction

Edge detection is a fundamental pre-processing step in image processing whose goal is to identify points corresponding to the object boundaries present in the digital

Max Mignotte mignotte@iro.umontreal.ca image. This low-level vision task which preserves the important structural properties of an image and changes its representation into something that is easier to analyze is often the preliminary and also the crucial step in the development of many image understanding algorithms and computer vision systems such as object localization/ recognition [1-3] or 3D reconstruction problems [4, 5].

Within this context, the availability of the Berkeley Segmentation Dataset (BSDS300) [6] in which a wide variety (300) of natural color images have been manually segmented by multiple contributors, has allowed to measure, with good statistical confidence, the performance of several edge or contour detection algorithms proposed in the literature. Among these, a significant number of methods [7–11], favorably evaluated on the BSDS300, are, in fact, mainly based on the probability-of-boundary (Pb) contour detector originally proposed in [6] by the authors of this dataset. In this latter contour detection approach, the local brightness, energy, color, and texture gradient features are first computed on oriented discs, are then independently optimized through a learning procedure, on the BSDS300 training set, and are finally combined in a learning logistic regression classification procedure in order to empirically define each pixel's likelihood of being on a contour.

In addition, the BSDS300 has also allowed to especially understand and to quantify the relative importance of color and texture in the contour detection process [6], the benefit of contour grouping [7, 8] and multiscale models and features over monoscale approaches [10, 12], the interest of combining regions (or global information) and boundary cues [9, 11, 13, 14], the benefit of learning the prior (and transition) distribution of pieces of contour shapes [15] or the advantage of learning to classify [16, 17] to name a few.

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Although they have not been evaluated or just partially on the BSDS300, other contour detection methods are worthy to be mentioned here, especially statistical methods which have the advantages to model, in a consistent statistical framework, the highly structured statistical properties of natural images (i.e., with possibly either an explicit mathematical model for edge, or contour structure or an image structural model, or some background statistics, or eventually noise and degradation models, etc.). In addition, these statistical methods are adaptive, data driven, are better suited to deal with noisy images and, moreover, inference can be efficiently used for the automatic and explicit estimation of the internal parameters of the model.

In this class of methods, the well-known Canny edge detector [18] assumes that edges are step functions corrupted by additive Gaussian noise. This algorithm is based on an optimal linear filter in the sense of three criteria (good detection/localization, and low multiplicity of the response to a single edge). In [19], an optimal edge detector, which revisits the analytical expressions of the three Canny's criteria is developed, in the case of discrete signals (see also [19] for numerous other variants of Canny edge detection approaches). Another statistical edge model has been considered in [20] in which the authors assume that curves are drawn from a Markov process and define a prior distribution both encouraging smooth contours and restricting the number of contours in an image. A statistical multiscale data-driven edge detector has also been proposed by Konishi et al. [21]. The statistical inference is simply expressed as a log-likelihood ratio test between the on- and off-edge non-parametric learned distributions of the filter responses. In [22], the authors present a global constrained Markov model for contours in images that also uses the conditional distributions of the gradient vector field on and off edges for the likelihood. The prior one is a Gibbs distribution and includes a smoothing parameter and all the internal parameters of the model are learned on-line using an iterative conditional estimation procedure. In [23], the a contrario framework allows the authors to model the Helmholtz principle which enunciates that relevant geometric structures such as contours have a very low probability to occur in a random context. Finally, the particle filter framework proposed in [15] allows both to express and learn the prior (and transition) distribution of pieces of contour shapes in such a way that the distribution automatically embeds efficiently a semi-local information of the contour structure via every possible contour variation and then to locally track with a particle filter, these pieces of contour shapes along contours.

Contrary to the statistical ones, biologically inspired edge detection models tend to exploit many structural features of the human visual system (HVS). Among these models, some low-level biological vision systems, try to replicate basic properties of the HVS, although some of them are not explicitly focused on the edge detection problem. For example, in [24], Hongler et al. propose a simple mathematical formalization of the dynamic retina concept [25, 26] for the edge detection problem in a vision system subject to vibration noise. A retina-inspired model for edge detection has also been proposed in [27] which both tries to simulate and implements the non-overlapping mosaic arrangement of retinal receptive fields as well as the dynamic retina concept. It is also worth mentioning the framework proposed in [28] which is based on the understanding of inhibitory mechanisms in biology and emphasizes the role of local information by combining classical edge detection with isotropic and anisotropic inhibition, thus achieving, as in [29], a kind of biologically motivated contrast operator, in the image processing context. In this two-step algorithm, the response of an edge detector is followed by an assessment based on the local context (i.e., the local response of the edge detector). This biologically motivated model, employing this inhibition mechanism, is reliable to detect contours of objects but cannot be efficiently exploited to reliably detect edges which belong to texture regions. A two-step model with an inhibitory mechanism, but well suited for the textural edge detection problem, has also been proposed in [30] and tries to simulate the response of P and M types of ganglion and lateral geniculate nucleus (LGN) cells in order to extract redundant subsets of fine and coarse edges. This information is then passed to a next stage (cortical level) and then processed in order to suppress (or inhibit) the response for edges within texture regions. Another way to model the response of LGN cells has also been recently proposed in [31], in which the authors propose a computational model of a simple cell, which combines the responses of model LGN cells with center-surround receptive field and that outperforms the traditional Gabor function model in contour detection. Finally, we can also mention the sparse coding model of cortical area proposed in [32], the combined use of retina and cerebral cortex modeling presented in [33] for the development of low-level image processing tasks such as motion analysis and video data structuring and the multifeature-based center-surround framework proposed in [34].

Apart from these models, focused on the edge detection problem (and for which a recent survey of methods, modeling biologically inspired aspects, is presented in [35]), biologically motivated local feature [36], color image [37], or keypoint [38] descriptors have been designed for object recognition, detection [39] and tracking [40] issues. In addition, low-level biologically inspired vision systems have been mainly proposed by the computer graphics community for the specific problem of displaying high dynamic range (HDR) images on traditional low dynamic range (LDR) devices. Among these so-called tone mapping methods which tend to replicate basic properties of the HVS, we can mention the research works that physically attempt to model the local sensitivity-adjusting process of the HVS for high contrast scenes. Among these HVS-based models of local adaptation, Pattanaik et al. [41] have used a multiscale decomposition of the image according to comprehensive psycho-physically derived filter banks and extensive psycho-physical data. The retinex model has also inspired several research projects [42-47]. Other interesting approaches include the local eye adaptation method [48] that compresses the dynamic range of the luminance channel by simulating the photoreceptor responses in the retina. Finally, let us also mention the recent tone mapping model proposed in [49] which tends to exploit the biologically inspired dynamic retina concept which is mathematically formalized via an image representation based on the specification of the statistical distribution of the non-local gradient magnitude in the HDR compressed image (Table 1).

The biologically inspired contour detection model presented in this paper tends to integrate three basic properties of the HVS; namely (1) the dynamic retina concept [25, 26], i.e., the small vibrations of the eyes and/ or the natural saccadic eve movement process (or saccades), that redirects the fovea's attention from one point of interest to another within the image, (2) the topological log-polar transformation (with its space-variant resolution) of the retinal image into its cortical projection [50-53] and finally, to a certain extent, (3) the optical illusion called Mach bands [54] that allows the HVS to increase the perceived change in brightness and makes it very sensitive to line structures (and thus, that makes the HVS inherently well suited for line detection). The remainder of this paper is organized as follows: Sect. 2 describes the proposed edge detection model and its links with the above-mentioned biologically inspired considerations. Finally, Sect. 3 presents a set of experimental results on the BSD300 and comparisons with existing segmentation techniques.

Table 1Overview tableproviding a (non-exhaustive)list and comparison of thedifferent contour detectionmodels validated (or not) on theBSDS300 in terms of F measure

Method (Refs.)	Category	Authors	Date	F-measure on BSDS300
[6]	Machine learning	Martin et al.	2004	Yes (0.65)
[7]	Statistical	Ren et al.	2005	Yes (0.64)
[8]	Graph-based	Zhu et al.	2007	Yes (0.64)
[9]	Graph and machine learning	Maire et al.	2008	Yes (0.70)
[10]	Statistical	Ren et al.	2008	Yes (0.68)
[11]	Graph and machine learning	Arbelaez et al.	2011	Yes (0.71)
[12]	Statistical	Widynski et al.	2014	Yes (0.71)
[13]	Machine learning	Fowlkes et al.	2003	Yes (0.65)
[14]	Graph and machine learning	Fowlkes et al.	2004	Yes (NA)
[15]	Statistical	Widynski et al.	2012	Yes (0.68)
[16]	Machine learning	Dollar et al.	2006	Yes (0.66)
[17]	Machine learning	Mairal et al.	2008	Yes (0.66)
[18]	Statistical	Canny	1986	Yes (0.58)
[<mark>19</mark>]	Statistical	Demigny	2002	No
[20]	Statistical	Felzenzwalb et al.	2006	Yes (NA)
[21]	Statistical	Konishi et al.	2003	No
[22]	Statistical	Destrempes et al.	2004	No
[23]	Statistical	Widynski et al.	2011	No
[24]	Biologically inspired	Hongler et al.	2003	No
[27]	biologically inspired	Roka et al.	2007	No
[28]	biologically inspired	Griorescu et al.	2003	No
[29]	biologically inspired	Itti et al.	1998	No
[30]	biologically inspired	Joshi et al.	2006	Yes (0.59)
[31]	biologically inspired	Azzopardi et al.	2012	No
[32]	biologically inspired	Spratling	2010	Yes (0.61)
[33]	biologically inspired	Benoit et al.	2010	No
[34]	biologically inspired	Yang et al.	2014	Yes (0.62)
[37]	biologically inspired	Zhang et al.	2012	Yes (0.68)

2 Proposed model

2.1 Log-polar cortical mapping of the retinal image

One interesting feature of the HVS is the topological transformation of the retinal image into its cortical projection (termed the conformal cortical mapping). More precisely, the input image, projected on the retina of the eye is reconfigured onto the (primary visual) cortex by a process similar to a log-polar mapping before it is examined by the brain. This property is due to the fact that, in humans and primates, the center of the retina (i.e., the fovea) has a much greater spatial resolution than the periphery, with a greater density of retinal cells with a sampling period increasing almost linearly with the distance from the fovea (see Fig. 1) [50–53]. With this linearly space-variant sampling structure, the information received by the primary visual cortex can be described through a log-polar mapping of the retinal stimulus (see Fig. 2). This log-polar mapping has been proposed as a very appropriate space-variant imaging model in active vision applications. This biologically inspired transformation model has several advantages and facilitates some visual tasks. For example, it can provide an efficient data reduction without a subsequent loss in perceptual information [52, 56], offers a good trade-off among large visual field and reasonably high resolution, preserves the oriented angle of intersection between two curves, and simplifies rotational and origincentered rotations and scalings become simple shifts in the cortical image (a useful property for scale and rotationinvariant pattern recognition [57]). In addition to these pattern recognition problems, this transformation also allows to facilitate the estimation of the time to impact from optical flow [58]. Log-polar transform is also an appealing transformation as it results in a foveated image (i.e., a smoothly space-variant resolution image) without blocking artifacts. In addition, it depicts in great detail the



Fig. 1 Graphical representation of the space-variant sampling structure of the fovea (center of the retina) with a much greater spatial resolution than the periphery, with a greater density of retinal cells. Within the fovea, the sampling period becomes almost constant (taken from [55])



Fig. 2 Log-polar transformation. Any point (x, y) (i.e., [column, row]) of the scene in the image plane (*left*) can be expressed in terms of (ρ, θ) in the cortical plane (*right*) by $(\log(\rho), \theta)$ with $\theta \in [0, 2\pi)$. In this example, the log-polar transform is centered at the center of the image. We can notice that concentric *circles* and radius lines in the Cartesian plane (*left*) are mapped respectively to *vertical* and *horizontal* lines in the cortical plane (*right*)

region where the focus of attention (corresponding to the reference center of its transformation) is (see Fig. 3).

2.2 Dynamic retina concept

Another interesting feature of the HVS is the presence of small vibrations of the eyes or natural saccadic eye movements, now well-known under the name of saccades. Our eyes are thus never still, even during fixation. This rapid and simultaneous movement of both eyes, from one still position to another, called saccade, is derived from a French word for "twitch" (namely saquier); saccade is a typical occurrence in visual perception, the eyes fixing on one point after another in the visual field [25, 26].

The primary function of saccade is to maximize information processing within the high resolution region of the fovea [59]. Another reason is that the brain directs the eye to move in such a way as to foveate successively onto the different points of interest within the image. The attention of the fovea is reserved for those elements that contain "essential information" necessary for the perception of the scene. By locating interesting parts of the scene, i.e., by redirecting the fovea from point of interest to another point of interest within the image, the brain is able to reconstruct a coherent interpretation and a mental three-dimensional (3D) "map" of the scene (based on a combination of foveal details and generalized low-acuity information acquired from the eye's periphery). A more sophisticated hypothesis for the role of saccades, in visual exploration, is that we saccade to areas which are expected to have useful spatial information for the interpretation of shapes or structures. We would therefore expect the eye to saccade to those



Fig. 3 *Top* original image and image showing $N_c = 5$ centers of reference (taken on the diagonal of a rectangular window, centered on the image and whose size is 80 % the size of the original image) associated to each log-polar transformation and inverse log-polar

features which are most useful for this task [25, 59–61]. In addition, saccades and microsaccades are part of the oculomotor strategy by which the visual system acquires fine spatial detail [62].

When scanning a stationary object, the eye alternates between fixations and saccades in the visual field (see Fig. 4). During each fixation on a given point of view or (point of) interest, the cortical or log-polar mapping is then built with this selected point of interest as center of reference for this log-polar transformation. During visual exploration, a series of saccade-fixation sequence (termed usually as a scanning saccade) is initiated and leads to a sequence of cortical mappings, to be examined by the brain, with these different points of interest as different centers of reference. From this sequence of cortical mappings, the brain fuses this information in order to acquire an accurate estimation and 3D understanding and interpretation of the different shapes and structures present in the scene. The process of retaining information across a scanning saccade is called trans-saccadic memory and the process of integrating information from more than one fixation is called trans-saccadic integration [63].

mapping transformation from the third log-polar mapping presented below (using a bi-linear interpolation). *Bottom* image mapped in logpolar domain w.r.t. these above-presented five different centers of reference



Fig. 4 By Yarbus [25]. The *right diagram* shows eye movement traces while a subject explores a picture of the bust of Nefertiti (*left*). While viewing a stationary object, the eye alternate between fixations and saccades. Each saccade leads to a new fixation (each *dot* represents a unit of time). Typically, the eye makes approximately 3 saccades per second, fixating on each point of interest for 300 ms at a time. The set of saccades occupy 10 % of the total viewing time. Yarbus [25] noted that the attention of the fovea is reserved for those elements that contain "essential information" necessary for the perception of the scene. The "less essential information" is ignored by the fovea and obtained by the lower resolution periphery. From only a small percentage of the visual field captured in high-acuity, the subject is able to reconstruct a useful understanding of the object on the scene

In our application, in order to replicate the sequence of cortical mappings obtained by the scanning saccade process i.e., from different points of view (of the image) which will be examined by the visual cortex, we have simply considered a fixed number of cortical (log-polar) mappings each one with respect to (w.r.t.) a different center of reference equally spaced on the diagonal segment located at the center of the image plane (see Fig. 3).

2.3 Lateral inhibition effect

Another interesting feature of the HVS is the Mach bands or lateral inhibition effect (LIE), named after the physicist Ernst Mach who first observed and studied them more than a century ago. Due to the inherent spatial high-pass filtering performed by the HVS on the luminance channel of the image captured by the retina, this LIE (or center-surround antagonism) allows to exaggerate the differences between neighboring areas of slightly differing shades of gray along the boundaries, thus naturally increasing the contrast-tonoise ratio and enhancing edge and straight lines detection by the HVS (see [64] p. 45 and [65] claiming that lateral inhibition of neurons in visual cortex allows contrast discrimination of oriented patterns). More generally, this phenomenon shows that the local spatial context of a contour significantly affects the global saliency of the contour and more formally, it approximates a second order derivative (i.e., a Laplacian) of the edge signal thus producing an enhanced edge with first an undershoot (i.e., a slight decrease in brightness compared to the true physical value) and then an overshoot in brightness.

In the context of the visual processes, the LIE is in fact known to occur in the early stages of visual information processing in biological systems; not only in the retina (thus in the image plane) but also in certain areas of the visual cortex [66, 67], thus in the cortical domain [68–70] or in conjunction with a (neural image and a) log-polar mapping (see Sect. 2.1). By recalling that each line segment in the log-polar plane gives a circular contour fragment in the image plane, the LIE, within the context of logpolar conformal mapping, will result in the enhancement of the image contours via (more precisely) the enhancement of all contour fragments of the boundaries of objects present in the image.

Let us note that smoothly curved contour can be generally handled as concatenations of (small) straight segments [71]. Nevertheless, even if many contours of manmade objects and shapes accept an economic description in terms of straight lines with the interesting ability to abstract away unwanted or useless details [72], it is important mentioning that a contour detection algorithm, on the original (Cartesian) image, based solely on the simple extraction of line segments would not give a competing edge detection algorithm (see Sect. 3.2 where this statement is evaluated, in term of F-measure, i.e., a measure that trades off precision versus recall, on the test set of the BSDS300 [73]).

In biological systems or in a visual exploration leading to a sequence of fixations creating a sequence of log-polar transformations w.r.t. different centers of reference, each portion of smooth curved contour can be viewed (or logpolar transformed) as a straight line contour in the cortical domain and we will exploit, among other things, this property. Indeed, a sequence of log-polar transformations (w.r.t. different centers of reference) has some properties that make it useful to detect curved contour segments. First note that curved contours with a concentric circle shape in the Cartesian image become a single straight vertical line in the cortical plane since the constant radius ρ of the circle gives a constant for all θ coordinate. Similarly, radial lines in the image plane which have constant angle but variable radius, result in a map of horizontal lines (see Fig. 2). Third, it is always possible to find a center of reference, or equivalently; a point of view or (point of) interest, for which this log-polar transformations will transform a given curved contour fragment into a straight line segment (see Fig. 5). Consequently, each curved contour segment can be approximated by an arc of circle with a given radius value and, each arc of circle portion is transformed into a straight line segment in the cortical plane with an appropriate reference center corresponding to the center of this arc of circle.



Fig. 5 *Top* curved contour fragment in the Cartesian image plane. *Bottom* three (cropped portion of) different log-polar deformations for which each contour fragment is transformed into a straight line segment

In order to simulate the LIE in the cortical domain, for the purpose of contour detection, we thus decide to extract straight line segments in the cortical image, and to this end, we resort to the fast line segment detector (LSD) recently introduced in [71] which is a linear-time line segment detector that gives sub-pixel accurate detection results for a controlled pre-determined number of false detections according to the a contrario principle (nevertheless, it is worth noting that our contour detection procedure remains independent of the choice of the underlying line detector). In contrast to classic edge detector, this algorithm defines a line segment as a rectangular region whose points share roughly the same image gradient angle. This algorithm is very efficient to detect line segments based on the empirical discovery made by Burns et al. [74] showing that connected (rectangular) regions with common orientation would almost always coincide with straight edges.

Finally, it is worth mentioning that the LIE simulation, within the context of a log-polar or cortical mapping, has been initially investigated in [75] in 1988 (and never after that) for the edge enhancement problem. In this latter simulation, a negative feedback system in one dimension (introduced in [76]) is exploited in order to simulate the way in which receptors interact in a negative inhibitory manner.

2.4 The proposed biologically inspired edge detection model

Our edge detection approach attempts to model these aforementioned biological structural features of the HVS.

In order to replicate the scanning saccade process, achieved during a visual exploration of an image (see Sect. 2.2), we have simply considered a sequence of N_c log-polar transformations or cortical mappings, w.r.t. N_c different equally spaced centers of reference (i.e., points of interest) taken on the diagonal of a rectangular window, centered on the image (and whose size is 80 % the size of the image, see Fig. 3). Each center of reference thus defines a logpolar mapping associated to a different point of view within the image plane. This sequence of cortical mappings, equivalent to the information of the retinal stimulus received by the primary visual cortex, will possibly transform, for one of them, a given curved contour fragment into a straight line segment (see Fig. 5) which will be then efficiently detected by the LSD algorithm [71]. In fact, it will always be true, at least locally; a smoothly curved contour will be often efficiently approximated by concatenations of small straight segments.

In order to only consider straight line segments delineating the boundary of two textured regions, we estimate, for each cortical mapping, an edge potential map $\Psi(.)$, in the textural sense [77]. This edge map will be used to find the most likely straight line segments effectively delineating two different textured regions. More precisely, in our model, we will retain the first N_s line segments of the LSD algorithm with the highest average potential value (computed over all the pixels belonging to the line segments).¹ This edge potential map requires to compute, at each pixel, the following potential or gradient distance

$$\mathcal{D}(h_{y-(N_w/2),x}, h_{y+(N_w/2),x}) \\ + \mathcal{D}(h_{y,x-(N_w/2)}, h_{y,x+(N_w/2)})$$
(1)

where *h* is the N_b -bin re-quantized local color histogram, located at row *y* and column *x* [77], and $\mathcal{D}(h_{x-d,y}, h_{x+d,y})$ is the L_1 norm between vectors (or bin descriptors) $h_{x-d,y}$ and $h_{x+d,y}$ computed on a squared N_w -size window centered respectively at location (x - d, y) and (x + d, y) [77]. This textural gradient map assumes simply that a texton (i.e., the repetitive character or element of a textured image, also called a texture primitive) is herein characterized by a mixture of colors or more precisely by the values of the requantized (local) color histogram. This model is simple to compute, allows significant data reduction while being robust to noise and local image transformations and has already demonstrated all its efficiency in region-based segmentation procedures [77, 78].

At this stage, we have a sequence of N_c sets of straight line segments (delineating two textural regions) for each cortical mapping (w.r.t. their respective given center of reference). Each line segment is associated to a mean potential value which define a confidence level that the line segment belongs to a contour in the textural sense. In order to finally fuse or reconstruct the final edge detection map of the input plane image from these N_c sets of straight lines detection in the space-variant log-polar domain, thus simulating and taking into account edge detection at different detail levels in the image (i.e., with foveal details and lowacuity information acquired from the eye's periphery), we carry out an inverse log-polar transformation and a simple averaging technique weighted by the above-mentioned potential value estimated for each line segment candidate. This finally defines a soft contour map which is then normalized between 0 and 1. A non-maximum suppression step is then employed to produce thin contours [11, 18].

In order to make our edge detection procedure a bit more robust, we resort to a similar strategy described in [79] (used for the region-based segmentation problem) which consists in repeating our segmentation process, in this case, our line segment detection on each log-polar mapping, expressed for different (non-linearly dependent)

¹ This detection procedure, between simple and textural edges, is somewhat similar to the integration and surround inhibition mechanism proposed in [30] allowing to discard irrelevant edges within texture regions.

Fig. 6 The general framework of the proposed algorithm visually describing the trans-saccadic memorization step composed of two sub-parts; namely (from *top* to *bottom*) (1) a sequence of cortical mappings (equivalent to the information of the retinal stimulus received by the primary visual cortex), or log-polar transformations w.r.t. different equally spaced centers of reference (or points of view/ interest within the image plane). (2) A detection step of the most likely straight line segments delineating two different textured regions (simulating the integration and surround inhibition mechanism allowing to discard irrelevant edges within texture regions). Finally, a trans-saccadic integration (or accumulation) step, allowing to fuse these different above-estimated edge maps, thus simulating and taking into account edge detection at different points of views and detail levels in the image plane

color spaces. In addition to the log-polar transformation, which facilitates the edge detection procedure (i.e., the detection of curved contour fragment after the inverse logpolar transformation), the use of different color spaces may also help the contour detection procedure. Indeed, with this strategy, small and adjacent regions of pixels with similar color in a given color space and for which a line segment detector cannot efficiently separate could produce a better estimation in another color space in which these two regions could have a more distinct color difference. Equivalently, these different color spaces, can be viewed as different image channels provided by various sensors or captors [79]. The same strategy can be used for different scale transformations for the same reasons. The scale transformation is already an intrinsic (internal) parameters of the LSD algorithm which proposes to achieve a line segment detection for a given resolution level of the input image.

In the same idea to exploit different color spaces or scale transformations in order to improve the final contour detection result, we will see that the addition of the Cartesian representation of the image to this set of (log) polar transforms can also further improve the result (see Sect. 3.2).

2.5 The BIEDA algorithm

Algorithm 1 shows a pseudo-code of the proposed final biologically inspired edge detection algorithm (BIEDA). Besides, Fig. 6 visually describes the two main parts of the model, namely; the trans-saccadic memorization and integration steps.

Starting from a 2D accumulation matrix *J*, whose size is equal to the image size and whose all pixel values are initially set to zero, the routine ACCUMULATE (\mathcal{L}_{N_s}) consists in accumulating, for each pixel value at location (x, y) of *J*, its preceding value and the mean edge potential of each line segment $\in \mathcal{L}_{N_s}$ crossing the pixel of coordinate (x, y) (see Eq. 2). In our application, better results are given with a geometric mean which allows to somewhat suppress



the spurious potential values while preserving the correct one, namely,

$$J(x,y) = \sum_{cs \in \mathcal{CS}, sc} \log_2(1 + \mathcal{L}_{N_s}(x,y)) \quad \forall x,y$$
(2)

The routine AVERAGING $_{k \in [0,...,N_c]}$ consists in (pixel-wise) averaging all the N_c edge potential images resulting from the inverse log-polar deformation w.r.t. its reference center.

Algorithm 1 BIEDA

Input: A (plane) image $I(x, y)$ (in RGB) Output: A soft contour map $O(x, y)$				
N_c Nb. of log-polar transf. (or centers of refer. c) N_s Nb. of considered line segments of the LSD with the highest potential value N_{sc} Nb. of scales for the LSD CS Set of considered color spaces				
$ \begin{array}{ll} \mathcal{P}_{c}(I) & \text{Log-polar map of } I \text{ w.r.t. the ref. center } c \\ \mathcal{P}_{c}^{-1}(.) & \text{Inverse log-polar w.r.t. the ref. center } c \\ \Psi(J) & \text{Edge potential map on the image } J \\ \text{LSD}_{sc} & \text{Line Seg. Detect. (with scale parameter } sc)} \\ & \text{gives in output a set of line segments } \mathcal{L} \end{array} $				
. Initialization:				
Build a list of N_c points $\{c_1, \ldots, c_{N_c}\}$ taken on a liagonal of a rectangular window centered on I $k \leftarrow 1$				
Trans-saccadic memorization				
k < N do				
• Compute $\mathcal{P}_{c_k}(I)$ & EXTRAPOLATION $[\mathcal{P}_{c_k}(I)]$ • Compute the edge potential $\Psi[\mathcal{P}_{c_k}(I)]$ • Init. the 2D accumulation matrix J to 0				
for each color channel and each color space $cs \in CS$ of $\mathcal{P}_{c_k}(I)$ and each scale factor sc do				
$\mathcal{L} \leftarrow \text{LSD}_{sc} \text{ on } \mathcal{P}_{c_k}(I)$ $\mathcal{L}_{N_s} \leftarrow \text{Select the } N_s \text{ line segments} \in \mathcal{L} \text{ with}$ the highest mean edge potential $\Psi(.)$ $J \leftarrow \text{ACCUMULATE}(\mathcal{L}_{N_s}) [\text{see Eq. (2)}]$				
• $\mathcal{K}_{c_k} \leftarrow \mathcal{P}_{c_k}^{-1}(J)$ • $k \leftarrow k+1$				
3 Trans-saccadic integration:				
$O \leftarrow \text{AVERAGING}_{k \in [1, \dots, N_c]} \{ \mathcal{K}_{c_k} \}$				
The routine EXTRAPOLATION performs a spatia				

The routine EXTRAPOLATION performs a spatial extrapolation of the log-polar image at spatial locations where $log(\rho)$ (i.e., the logarithm of the Euclidean distance between a given center of reference and a pixel in the Cartesian image) cannot be computed because the pixel is located outside the image plane (see Fig. 7). It prevents edges from being wrongly detected along these false boundaries by the LSD algorithm. In our application, this extrapolation scheme is performed by sweeping the log-polar image in lexicographical order and to replace, for each pixel with no intensity value (thus corresponding to a pixel coordinate outside the Cartesian image),



Fig. 7 EXTRAPOLATION routine achieved on the first log-polar mapping presented in Fig. 3 (at *left*) and applied at spatial locations where a pixel value in the Cartesian image cannot be computed because its coordinates are outside the image plane

its grey value, by the average of non-null pixel values located in a 8-neighborhood system. Let us note that this routine is not mandatory since simple alternative strategies are possible and simply consists in either discarding edges which falls on the border of the final (Cartesian) contour image O(x, y) or to set to zero the edge potential $\Psi(.)$ (see Eq. 1) for the pixel locations corresponding to these false boundaries.

2.6 Discussion

Without biological consideration, we can also view the proposed algorithm as a voting scheme for the detection of (eventually small) circular arcs or contour fragments delineating the boundary of two textured regions.² Contrary to a Hough-style approach, which is dedicated to the detection of (whole) parametric curves, our algorithm aims at detecting (possibly small) straight segments in the log-polar domain, or

² It is important to recall and understand that $N_c = 10$ (log) polar maps cannot (obviously) transform all long (possibly circular) contour fragments into straight lines. When the polar transforms are not able to ensure this property, these contour fragments are just approximated by concatenations of small straight segments in the log-polar domain or equivalently by small circular arcs, in the Cartesian domain, which accumulate in the final soft contour map. It is worth also mentioning that we have tried, without success, to find a more optimal way to distribute the N_c centers of the log-polar transforms within the image, with different patterns such as the set dots uniformly distributed along a spiral centered at the center of the image or other patterns. The only conclusion I reached is that the N_c centers of references should not be to close together (certainly in order to ensure some diversities in the polar transforms), not to close to the edges of the image (certainly to ensure that the polar image is not too distorted) and the performance in term of F-measure of good detection are all the more better than N_c is high up to certain extent (see Fig. 8).



Fig. 8 Evolution of the F-measure score for the Algorithm 2, as a function of respectively, the number of log-polar transforms and the number of different *color spaces* (in each case, the other parameters of the model have been kept identical)

equivalently, small circular arcs or parametric curve fragments in the Cartesian domain (after the inverse polar transform). To this end, the proposed algorithm accumulates, for each polar view and color channels, color spaces or considered scale factors, these contour fragments, as a voting scheme in the Cartesian (image) domain, in an accumulation matrix, in order to achieve a final soft contour map. Another way to understand the proposed algorithm is to consider it as a two-step bottom-up contour detection procedure involving

- an amplification step, via our accumulation map and accumulation procedure (see Trans-saccadic memorization part of Algorithm 1) which aims at enhancing or amplifying (almost circular) textural contour fragments, first detected in the log-polar plane via straight segments and then in the Cartesian (image) plane (after the inverse polar transform) (Fig. 9).
- 2. a final denoising step, via our averaging procedure (see Trans-saccadic integration part of Algorithm 1) which aims at removing noise and spurious edges.

3 Experimental results

3.1 Set up

For the edge potential map estimation (see Sect. 2.4 and Eq. 1), parameters are also those proposed in [77, 78], i.e., $N_w = 7$, $N_b = 5$ and d = 3 (see especially [77] in Fig. 8a, for the experimental study and the rationale behind the



Fig. 9 Examples of edge potential maps obtained for each log-polar transform (w.r.t. its center of reference) on the natural image shown in Fig. 3. *Top* edge potential maps in the log-polar domain. *Bottom* edge potential maps obtained in the Cartesian domain after an inverse log-polar transform w.r.t. its center of reference. We can notice that the edge potential maps obtained for each log-polar transform are

obtained at different (spatially variant) resolutions and levels of details. In addition, these edge potential maps are different and complementary; this diversity will allow that the trans-saccadic integration step, via the simple averaging process, will insure a reliable final soft edge map



Fig. 10 Polar transformation w.r.t. the same center of reference as the log-polar transform shown in Fig. 7

value of these two parameters in their ability to detect a reliable potential map on the Berkeley database).

We will see later in this Section that the performance measure of good detection are all the more better than N_c ; the number of log-polar transforms (w.r.t. its center of reference) and the number of considered color spaces in CSis high. In order to limit the computational requirement of our algorithm, we set $N_c = 10$ (see Fig. 3 and ²), $N_{sc} = 4$ (number of scales) and $CS = \{\text{RGB, HSV, YIQ, XYZ, LAB, LUV}\}$ (see Algorithm 1).

In our application, N_s , the number of line segments of the LSD, considered with the highest (textural) potential value, is an important internal parameter of our algorithm to be estimated. To evaluate our algorithm and to estimate this important internal parameter, we replicated the scenario proposed in [6–16, 73], using the BSDS300 and the F-measure.³ In order to ensure the integrity of the



Fig. 11 Non-thickened final soft contour map (of the input image shown in Fig. 3) consisting in averaging all the N_c edge potential images coming from the inverse log-polar, polar deformations and from the Cartesian image

evaluation, the internal parameter N_s of our algorithm is tuned on the train image set (pre-defined by the author of the BSDS300), by doing a local discrete grid search routine, with a fixed step size, on the parameter space and in a given range of parameter values (namely, $N_s \in [30 - 300]$ [step size: 30]. We have finally found that $N_s = 180$ allows us to ensure a maximal F-measure score on the training set. This estimation of N_s is then used, as internal parameter, to benchmark our algorithm on the independent test set.

Before all, we show, in Fig. 11, the non-thickened final soft contour map which consists in (pixel-wise) averaging all the N_c edge potential images (coming from the inverse log-polar, polar deformations and from the Cartesian image). We can notice that the accumulation of numerous (different size) almost circular fragments, coming from the detection of straight segments in the polar or log-polar planes and straight segments directly (in the image plane) creates a smooth edge potential map without line or circular artifacts.

3.2 Comparison with state-of-the-art methods

First, we have evaluated the algorithm as summarized in Algorithm 1 but also the strategy of combining $(N_c/2)$ logpolar transforms with $(N_c/2)$ (space-invariant resolution) polar transforms on the test set of the BSDS300. The visual differences between log-polar and polar deformation (w.r.t. a same center of reference) are shown in Figs. 7 and 10 for a given natural image.

In addition, as already said in Sect. 2.3, in the context of the visual processes, the LIE is in fact known to occur not only in the cortical plane but also in the retina (thus in the Cartesian image plane). Therefore, we have also evaluated the benefit of adding the input Cartesian image to this set of log-polar and polar transforms (we refer to this algorithm

³ The F-measure, proposed by Martin et al. [73], is deduced from the Precision/Recall values and characterizes the agreement between region boundaries of two segmentations. The precision measure (P) is defined as the fraction of detections that are true boundaries (this measure is then low when there is significant over-segmentation, or when a large number of boundary pixels have poor localization). The recall (R) measure gives the fraction of true boundaries detected. A low recall value is typically the result of under-segmentation and indicates failure to capture salient image structure. Thus, Precision quantifies the amount of noise in the output of a detector, while recall quantifies the amount of ground truth detected. The performance of a boundary detector providing a binary output is represented by a point in the precision-recall plane. If the output is a soft boundary image, a parametric precision-recall curve expresses the compromise between absence of noise and fidelity to ground truth as the main parameter of the boundary detector varies. Precision and recall can be combined in a single quality statistic measure, the F-measure (F = 2PR/(P + R)), defined as their harmonic mean and as a measure of performance combining both precision and recall. The notation F@(recall, precision) represents the value of the highest F performance measure (of a binary classifier) existing on its precision-recall (or ROC) curve at coordinates "@", the measure of its recall performance (on x axis) and its precision performance (on y axis). This highest F-measure on a Precision-Recall curve is used as a summary statistic for the performance of the detector on a set of images.

as Algorithm 2). Indeed, even without this aforementioned biological justification, it is worth recalling that the Cartesian image plane may give an interesting spatial configuration of the image scene exhibiting, in some parts of the image, straight line segments for contours only existing in the original Cartesian plane. We will check, to what extent, this modification will improve the efficiency of our basic procedure summarized in Algorithm 1.



Fig. 12 *Top* F-measure scores by several other state-of-the art edge/contour detection methods on the BSDS300 (illustration is adapted from [15]). *Bottom* F-measure scores for different variants of our Algorithm 2. Namely; F-measure curve by considering; (1) only the Cartesian image, with one color space and one scale and weighted by our edge potential map (in the textural sense), (2) $N_c/2$ log-polar transforms, (3) $(N_c/2)$ log-polar with $(N_c/2)$ polar transforms, (4) the BIEDA model, i.e., by adding the input Cartesian image to the set of $N_c/2$ log-polar and polar transforms (in cases 2–4, the other parameters of the model have been kept identical)

By considering only the N_c log-polar transforms, we obtain (i.e., for Algorithm 1) an F-measure score at 0.65 (recall: 0.69, precision: 0.61) on the 100 test images of the BSDS300. By combining $(N_c/2)$ log-polar with $(N_c/2)$ polar transforms, we obtain an F-measure score at 0.67 (recall: 0.71, precision: 0.65). Finally, by adding the input Cartesian image to this set of log-polar and polar transforms, we obtain an F-measure score at 0.69 (recall: 0.72, precision: 0.66) for a global optimal threshold of t = 0.52(for gray levels lying between 0 and 1). As already said, the use of the original Cartesian image, in our application, is justified since many contours of man-made objects and natural shapes, in the original Cartesian image, will consist of straight lines (which will possibly transform into curves in polar or log-polar domain). Since this (slight) improvement is not achieved at the expense of too much computational cost, we consider this algorithm (combining log-polar, polar, and the Cartesian image) as a baseline for comparison purposes in the following (Algorithm 2). By comparison, if we consider only the Cartesian image, with one color space and one scale, we obtain an F-measure score at 0.53 (recall: 0.43, precision: 0.67). A low recall value is typically the result of under-segmentation and indicates that this strategy fails to detect important edges in the image (in this case, mainly the edges associated to the highly curved contours). Figure 12 (at bottom) shows several F-measure curves for these aforementioned variants of our Algorithm.

We can notice (see the precision–recall curves shown in Fig. 12), that our BIEDA model performs well, compared to the best existing state-of-the-art edge or contour detectors existing in the literature (namely the gPb [11] and the PFCD [15]) with an F-measure score at 0.69 (recall: 0.72, precision: 0.66) on the 100 test images of the BSDS300. Full results of our final algorithm are reported in Table 2 including the Optimal Dataset Scale (ODS) F-measure score which is obtained using the global optimal threshold on the (100 test images of the) BSDS300, i.e., the so-called

 Table 2 Comparison of F-measure [73] results obtained on the BSDS300 [6]

	ODS	OIS
Human	0.79	0.79
BIEDA	0.69	0.70
gPb (Maire et al. [9])	0.70	0.72
PFCD (Widynski et al. [12])	0.68	0.69
Canny [18]	0.58	0.62

ODS is the optimal scale on the dataset (or the global optimal threshold [t = 0.52] estimated on all the test images [11]) and OIS is the optimal scale on each image (or optimal threshold on each test image [11])



Fig. 13 Examples of soft contour maps obtained by the proposed BIEDA scheme (Algorithm 2) after a non-maximum suppression step on some images of the test set of the BSDS300 (and the image

number 134052). We obtain for the test set of the BSDS300, an F-measure score at 0.69 (recall: 0.72, precision: 0.66) for a global optimal threshold of t = 0.52 (for gray levels lying between 0 and 1)

(usually referred as) F-measure score along with the Optimal Image Scale (OIS), i.e., the F-measure score obtained using the optimal threshold on each image. Fig. 13 illustrates a few contour detection results obtained by the proposed algorithm after a non-maximum suppression step. Visually, we can notice that the edge maps generated by our approach is a bit over-segmented comparatively to the gPb detector (and its numerous variants).

This is confirmed by the obtained score 0.69@ (0.72, 0.66) with an ODS threshold 0.52 compared to the score obtained by the gPb detector 0.70@ (0.71, 0.68) with an ODS threshold 0.13 showing, in our case, a greater value for the recall and the threshold value.

Finally, we have evaluated the performance of our algorithm as a function of, respectively, N_c the number of polar and log-polar transforms and the number of different



Fig. 14 Examples of different ways of distributing the N_c centers of the log-polar transforms. From lexicographic order, the following F-measure scores are obtained (in each case, the other parameters of

color spaces (in each case, the other parameters of the model have been kept identical). Results are summarized in Fig. 8 and shows the benefit of doing and averaging (up to a certain extent) several transformations possibly expressed in different color and coordinate spaces (Fig. 14).

3.3 Algorithm and discussion

Figure 14 shows us different ways of distributing the N_c centers of the log-polar transforms within the image and the final F-measure score obtained in each case (the other parameters of the BIEDA model have been kept identical). The only conclusion we can reach is that the N_c centers of references should not be to close together (certainly in order to ensure some diversities in the polar transforms). Else, we can notice that the shape of the distribution pattern seems not very important.

In addition, in order to show that bio-inspired geometric transforms outperforms other non-linear geometrical transforms for the specific edge detection problem, the BIEDA model has been tested by replacing the N_c polar and log-polar transforms by a set of $N_c(= 10)$ stretching

the BIEDA model have been kept identical): 0.6870, 0.6718, 0.6761, 0.6799, 0.6826, 0.6765, 0.6839, 0.6848, 0.6858, 0.6730, 0.6798, 0.6836, 0.6866

transforms (see Fig. 15) whose side of the stretch and the stretching factor was randomly chosen in the interval [0.50; 1.50]. In this case, the final F-measure score obtained is (with the other parameters of the BIEDA model remaining the same): 0.6693@ (0.7218, 0.6239) which is not bad at all but less than the score obtained with the set of (log)-polar transformations.

The edge detection procedure takes, on average, 1 min for an IntelCore i7, 3.2 GHz, 6403 bogomips and nonoptimized code running on Linux which is comparable to the gPb detector [11, 80] and to the PFCD detector [15]. Let us add that our algorithm and especially the set of logpolar or polar transforms, along with the line segment detection process can be easily computed in parallel, for example using the parallel abilities of a graphic processor unit (GPU) (embedded on most graphics hardware nowadays available on the market) [81].

In addition to the fact that our algorithm could benefit from any hardware based on multi-threaded CPUs or GPU cards, it is worth mentioning that, with a quite similar F-measure score compared to the state-of-the-art gPb-based contour detector, the precision and recall measures are



Fig. 15 Example of non-linear stretching transforms according to each of the four sides of the images with a stretching factor = 1.0 (i.e., representing the ratio between the width and the smallest stretched side)

 Table 3 Comparison of scores between the BIEDA and the gPb algorithms on the 100 test images of the BSDS300

	BIEDA	gPb
OIS Recall score	64	36
ODS Recall score	60	40
OIS Precision score	27	73
ODS Precision score	25	75
OIS F-Measure score	30	70
ODS F-Measure score	28	72

Each row points out the number of images of the test set that obtain the best score (OIS and ODS scores are respectively the score based on the optimal threshold obtained from each image and the one based on the global optimal threshold estimated on all the test images)

quite different for a given image compared to the measures obtained by the gPb algorithm (see Table 3). It means that these two methods perform differently and well for different images. This is not surprising since these two methods are, by nature, very different from each other. This fact may suggest that these two methods extract complementary edge information and, consequently, could be paired up or combined together to achieve better results.

Source code (in C++ language) of our algorithm with the set of contour detections obtained by our algorithm and the F-measure data (OIS and precision–recall curve for each test image with comparison with ground truth segmentations) are publicly available at the web site of the author in order to make possible eventual comparisons with future segmentation algorithms or different performance measures.⁴

4 Conclusion

In this paper, we have presented a new method for the edge or contour detection problem in natural images. The proposed biologically inspired model tends to exploit some important structural properties of the HVS and especially the neural mechanism controlling the natural saccadic eye movement process occurring during visual exploration/ search and the resulting (saccade fixation) sequence of logpolar transformations of the retinal image which finally corresponds to the information received by the cerebral (visual) cortex. In this log-polar domain, the contour detection problem is reliably facilitated since a given curved contour fragment may be possibly transformed into a straight line segment which will be then efficiently detected by a reliable line segment detection method. This edge detection model performs well (in term of F-measure) compared to the best existing state-of-the-art edge or contour detectors, remains simple to implement and perfectible by increasing the number of log-polar transforms (w.r.t. different points of view or centers of reference within the input image) or by dynamically set and/or adaptively selecting more appropriate points of view within the image. In addition, our edge detection model is easily parallelizable and thus remains especially well suited for the next-generation massively parallel computers and multi-core processors.

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⁴ http://www.iro.umontreal.ca/ \sim mignotte/ResearchMaterial/bieda. html.

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